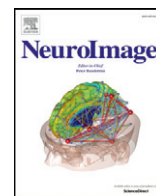


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Multi-subject and multi-task experimental validation of the hierarchical Bayesian diffuse optical tomography algorithm

Okito Yamashita^{a,b,*}, Takeaki Shimokawa^a, Ryota Aisu^{a,c}, Takashi Amita^d, Yoshihiro Inoue^d, Masa-aki Sato^a^a Neural Information Analysis Laboratories, ATR, 2-2-2 Hikaridai, Keihanna Science City, Kyoto 619-0288, Japan^b Brain Functional Imaging Technologies Group, CiNet, 1-4 Yamadaoka, Suita City, Osaka 565-0871, Japan^c Nara Institute of Science and Technology, 8916-5 Takayama, Ikoma, Nara 630-0192, Japan^d Medical Systems Division Research and Development Department, Shimadzu Corporation, 1 Nishinokyo-Kuwabaracho, Nakagyo-ku, Kyoto 604-8511, Japan

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ABSTRACT

Diffuse optical tomography (DOT) is an emerging technology for improving the spatial resolution and spatial specificity of conventional multi-channel near-infrared spectroscopy (NIRS) by the use of high-density measurements and an image reconstruction algorithm. We recently proposed a hierarchical Bayesian DOT algorithm that allows for accurate simultaneous reconstruction of scalp and cortical hemodynamic changes, and verified its performance with a phantom experiment, a computer simulation, and experimental data from one human subject. We extend our previous human case study to a multi-subject, multi-task study, to demonstrate the validity of the algorithm on a wider population and varied task conditions. We measured brain activity during three graded tasks (hand movement, index finger movement, and no-movement), in 12 subjects, using high-density NIRS and functional magnetic resonance imaging (fMRI), acquired in different sessions. The reconstruction performance of our algorithm, and the current gold-standard method for DOT image reconstruction, were evaluated using the blood-oxygenation-level-dependent (BOLD) signals of the fMRI as a reference. In comparison with the BOLD signals, our method achieved a median localization error of 6 and 8 mm, and a spatial-pattern similarity of 0.6 and 0.4 for the hand and finger tasks, respectively. It also did not reconstruct any activity in the no-movement task. Compared with the current gold-standard method, the new method showed fewer false positives, which resulted in improved spatial-pattern similarity, although the localization errors of the main activity clusters were comparable.

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1. Introduction

Functional near-infrared spectroscopy (fNIRS) is a noninvasive optical imaging technique that measures the changes in oxygenated and deoxygenated hemoglobin concentrations (hemodynamic changes) in response to changes in neuronal activity. fNIRS is sensitive to hemodynamic responses analogous to the blood-oxygenation-level-dependent (BOLD) signals found in fMRI, yet offers the advantages of low cost, easy portability, and the possibility of extending brain measurements to include such subjects as babies, elderly people, and patients with an implanted electronic device. It also permits measurements to be made

in ambient environments (for a historical review, see [Ferrari and Quaresima, 2012](#)).

The currently available fNIRS scalp topography methods have a couple of disadvantages that reduce the reliability of the results when used as a brain imaging method. First, the relative positions of the measurement channels to brain anatomy vary between subjects, and also between sessions within the same subjects. The activation foci consistently observed in the scalp topography do not necessarily indicate activation foci that consistently result from the same brain region. Second, fNIRS measurements are always affected by the hemodynamic changes in the scalp layer, and these changes may often dominate the contributions from cortical activity ([Kirilina et al., 2012](#); [Saager and Berger, 2005, 2007](#)). Recently, one study showed that most of the oxy-hemoglobin concentration changes measured from the forehead during a verbal fluency task were due to changes in scalp hemodynamics ([Takahashi et al., 2011](#)). Several signal processing methods for the removal of scalp artifacts have been proposed, these include the use of principle component analysis (PCA) ([Zhang et al., 2005](#)), independent component analysis (ICA) ([Kohno et al., 2007](#)), adaptive filters ([Zhang](#)

Abbreviations: fNIRS, functional near-infrared spectroscopy; DOT, diffuse optical tomography; HbR, deoxygenated hemoglobin; HbO, oxygenated hemoglobin; LE, localization error; AUC, area under the receiver-operating curve; SS, spatial-pattern similarity; FPA, false positive amount.

* Corresponding author at: Neural Information Analysis Laboratories, ATR, 2-2-2 Hikaridai, Keihanna Science City, Kyoto 619-0288, Japan.

E-mail address: oyamashi@atr.jp (O. Yamashita).

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et al., 2009, 2007), and short-channel regression (Gregg et al., 2010; Saager and Berger, 2005, 2007; Umeyama and Yamada, 2014; Zeff et al., 2007).

Diffuse optical tomography (DOT) is an emerging technology that may solve the above issues. It is a computer-assisted method for the three-dimensional reconstruction of images showing changes in cerebral hemodynamics. The technique uses a combination of high-density measurements, forward modeling, and an image reconstruction algorithm (Bluestone et al., 2001; Boas et al., 2004; Eggebrecht et al., 2014). High-density measurements with an inter-probe distance of around 10 mm allow multiple-distance channels and optical-path overlap between channels, which permits an increase in spatial specificity, in both the depth and surface directions. To exploit this increased spatial specificity, a forward model that quantitatively relates the activity inside the head tissue to the measured light intensity changes, is established by simulating a light migration process. An image reconstruction algorithm is then utilized to reconstruct a three-dimensional activity image from the observed light intensity changes. In principle, a reconstructed three-dimensional image allows for the separation and localization of scalp and cortical hemodynamic changes, improving the interpretation of results in terms of brain anatomy.

The quality of the reconstructed images depends on the image reconstruction algorithm, and a number of such algorithms have been proposed in previous studies. The image reconstruction problem is generally formulated as a linear inverse problem (Arridge, 1999; Boas et al., 2004), which is an underdetermined problem requiring a priori information to constrain possible solutions. One scheme for solving the inverse problem is the regularization approach, which uses a cost function consisting of the data fitting term and constraint terms representing a priori information (Boas et al., 2004; Cao et al., 2007; Culver et al., 2003; Lee et al., 2015). A DOT image is obtained by minimization of the cost function. Another approach is to use Bayesian modeling, which relies on a probabilistic model of observations and constraints called the likelihood function and prior distribution, respectively (Abdelnour et al., 2010; Guven et al., 2005; Shimokawa et al., 2012, 2013). A DOT image is obtained by computing the posterior distribution and utilizing the representative statistics of the posterior distribution (e.g., mean or mode). The probabilistic modeling and posterior computation developed in the Bayesian statistics (Gelman et al., 2014) provide a systematic way to compute meta-parameters (e.g., the regularization parameter) in the algorithm. This allows established knowledge to be incorporated into models in a more flexible manner.

Despite a variety of different image reconstruction algorithms, no research had proposed a DOT algorithm to accurately reconstruct both the scalp and cortical activity simultaneously, until we proposed the hierarchical Bayesian DOT algorithm (Shimokawa et al., 2013). Currently, a two-step approach is used for real experimental data, including visual, auditory, and resting paradigms (Eggebrecht et al., 2014; White et al., 2009; Zeff et al., 2007). In this two-step approach, scalp artifacts are removed by short-channel regression, which is then followed by cortical image reconstruction using the depth-compensation minimum norm method (Culver et al., 2003). As an alternative, our hierarchical Bayesian algorithm simultaneously reconstructs activity in the scalp and cortical layers using an individual head model. The key concept is a probabilistic model characterizing the distinct nature of the scalp and cortical hemodynamic changes. We assume a spatial smoothness prior for the scalp hemodynamics and a sparse-promoting prior for the cortical hemodynamics. This is made on the basis of the empirical observation that scalp hemodynamics change globally (Funane et al., 2014; Kohno et al., 2007; Zhang et al., 2005), but task-related cortical hemodynamics change rather locally. We have previously verified the performance of our algorithm using a two-layer phantom experiment and a computer simulation (Shimokawa et al., 2013). This was followed by experimental data from one human subject performing a right finger movement task (Yamashita et al., 2014).

In this work, we extend our previous human case study to a multi-subject and multi-task experiment, to test the validity of our algorithm on a wider population and different task conditions. A human case study demonstrated remarkable consistency between reconstructed cortical images and fMRI images (Yamashita et al., 2014); however, with consideration of inter-subject variability in light transmission and head anatomy, it remains unclear whether the previous single subject study can be generalized to a group level study. It is also unclear how our hierarchical Bayesian method performs with cortical activity of different sizes and amplitudes. To address these questions, we measured brain activity with high-density NIRS and fMRI acquired in different sessions, using 12 subjects, who performed three graded tasks. The three tasks were right hand movement, right index finger movement, and no-movement. These were selected to experimentally modulate the size and amplitude of the activations in the left primary motor cortex. We validated the performance of our algorithm using fMRI as a reference. In addition, we compared it with the two-step approach, which is the current gold-standard method for DOT (Eggebrecht et al., 2014).

1.1. Hierarchical Bayesian image reconstruction model

We originally proposed a hierarchical Bayesian sparse image reconstruction algorithm (Shimokawa et al., 2012), and later extended it to human functional brain imaging (Shimokawa et al., 2013). Here we briefly describe our model, while the image reconstruction algorithm is described in the Appendix A.

We first reconstruct images of the absorption changes at multiple wavelengths, and then convert these to images of the hemodynamic changes (oxy- and deoxy-hemoglobin concentration) using spectral extinction coefficients (Shimokawa et al., 2013, Eq. 13). Let $\mathbf{x} = (x_1, x_2, \dots, x_N)^T$ denote the absorption changes in the N voxels of the discretized head tissue and $\mathbf{y} = (y_1, y_2, \dots, y_M)^T$ the log-ratio of the light intensity changes measured by the M pairs of the source and detector probes on the scalp. Under the condition that the absorption changes are small relative to the baseline condition, the Rytov approximation leads to a linear relationship between detected light intensity changes \mathbf{y} and absorption changes \mathbf{x} (Arridge, 1999; Durduran et al., 2010; Shimokawa et al., 2012):

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \boldsymbol{\varepsilon}, \quad (1)$$

where \mathbf{A} is the sensitivity matrix and $\boldsymbol{\varepsilon}$ represents the measurement noise. As absorption changes occur predominantly in the scalp and cortex where blood vessels exist, we assume measurements are affected by the absorption changes in these two layers. Thus Eq. (1) can be rewritten as

$$\mathbf{y} = \mathbf{A}^c \mathbf{x}^c + \mathbf{A}^s \mathbf{x}^s + \boldsymbol{\varepsilon}, \quad (2)$$

where $\mathbf{A}^c, \mathbf{x}^c$ and $\mathbf{A}^s, \mathbf{x}^s$ are the sensitivity and absorption changes in the cortical and scalp layers, respectively. Assuming measurement noise $\boldsymbol{\varepsilon}$ follows a Gaussian distribution $N(0, \sigma^{-1}\boldsymbol{\Sigma})$, the forward model (2) can be written as the following probabilistic model:

$$\mathbf{P}(\mathbf{y}, \mathbf{x}^c, \mathbf{x}^s, \boldsymbol{\sigma}) \sim N(\mathbf{A}^c \mathbf{x}^c + \mathbf{A}^s \mathbf{x}^s, \sigma^{-1}\boldsymbol{\Sigma}), \quad (3)$$

where $\boldsymbol{\Sigma}$ is a scale-normalized noise covariance matrix computed from the data during the baseline period, and σ is the precision (inverse variance).

We assume the spatial smoothness and sparseness priors for the scalp and cortical absorption changes, respectively. For the scalp absorption changes, we implemented the spatial smoothness prior by assigning high probabilities to the small values of the spatial derivative of absorption changes \mathbf{z}^s as follows:

$$\mathbf{z}^s = \mathbf{L}\mathbf{x}^s, \quad (4)$$

$$\mathbf{P}(\mathbf{z}^s | \boldsymbol{\eta}) \sim N(0, \boldsymbol{\eta}^{-1}\mathbf{I}), \quad (5)$$

where \mathbf{L} is the discretized version of the spatial Laplacian operator. A parameter η , which is determined from the data, controls the extent of the spatial smoothness. As the prior of the cortical absorption changes, locally extended activation is represented by sparse absorption changes \mathbf{z}^c convolved with Gaussian smoothing operator \mathbf{W} as follows:

$$\mathbf{x}^c = \mathbf{W}\mathbf{z}^c \quad (6)$$

$$\mathbf{P}(\mathbf{z}^c|\boldsymbol{\lambda}) \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Lambda}^{-1}) \quad (7)$$

$$\mathbf{P}(\boldsymbol{\lambda}) = \prod_i \Gamma(\lambda_i; \bar{\lambda}_{0i}, \gamma_0), \quad (8)$$

where $\boldsymbol{\Lambda} = \text{diag}(\boldsymbol{\lambda})$, $\boldsymbol{\lambda} = (\lambda_1, \dots, \lambda_{N_c})'$ and $\Gamma(\lambda_i; \bar{\lambda}_{0i}, \gamma_0)$ is the gamma distribution with mean $\bar{\lambda}_{0i}$ and shape parameter γ_0 (assumed to be common to all voxels). The hierarchical prior distributions (7) and (8) promote the sparseness of \mathbf{z}^c by automatically adjusting all the elements of $\boldsymbol{\lambda}$ (called the relevance parameters) that control the amplitude range of absorption change in corresponding voxels (Faul and Tipping, 2002; MacKay, 1994; Wipf and Nagarajan, 2008).

Finally, a non-informative prior is assumed for σ, η to complete the full Bayesian formulation of our model:

$$\mathbf{P}(\eta) \sim \eta^{-1}, \quad (9)$$

$$\mathbf{P}(\sigma) \sim \sigma^{-1}. \quad (10)$$

The image reconstruction algorithm determining all the parameters $\mathbf{x}^c, \mathbf{x}^s, \sigma, \eta, \boldsymbol{\lambda}$ from data \mathbf{y} , can then be derived by inverting the above model using the variational Bayesian method (Attias, 1999; Sato, 2001).

2. Methods

2.1. Subjects

Twelve healthy, right-handed males (22–45 years old) participated in the study. Written informed consent was obtained from all participants before the experiments and they were paid for their participation. The experiments were conducted according to the Declaration of Helsinki and were approved by the Ethics Committee of the Advanced Telecommunication Research Institute International, Japan.

2.2. Subject tasks

All subjects participated in two experimental sessions conducted on different days; an fMRI experimental session was followed by a NIRS experimental session (from 2 weeks to 4 months apart). In both the fMRI and NIRS experiments, each subject conducted three graded tasks: a right hand gripping task, a right index finger extension task, and a no-movement task (abbreviated as HAND, FINGER, and NO conditions). Subjects were instructed to rhythmically open and close their right hand in the HAND condition, to rhythmically extend their index finger in the FINGER condition, and to keep their hand still and relaxed in the NO condition. Throughout the experiment, subjects kept their eyes closed and listened to beep sounds delivered every second, the tones of which indicated the timing of the task movement and the rest period (high tone for task, low tone for rest). In one run, the subjects repeated one of the three tasks, as instructed at the beginning of a run. Each run commenced with a 10-second rest period, followed by 15 trials of the task period (15 s) interleaved with rest periods (20 s). In the rest period, subjects remained quiet with their arm still. All the subjects conducted two experimental runs of the three tasks, resulting in a total of 30 trials for each task. At the beginning of the NIRS session, the brain activity of subjects was measured during the resting-state (eyes closed) for 1 min.

2.3. NIRS data acquisition

NIRS data were acquired using commercial NIRS equipment (FOIRE 3000, Shimadzu Corp., Japan) with electric amplifier gain and probe shape customized for high-density measurements. Using a custom-made holder, 12 source and 13 detector probes were placed on the left side of the scalp to cover the hand area of the primary motor cortex (Fig. 1(a) and (b)). We used a 5×5 square geometry, where the first and second shortest distances between source and detector probes were 13 and 29 mm, respectively. Because of a limitation with the measurement system, which only allowed for a maximum of 64 measurement channels, we recorded all the pairs of the second shortest channel (48 channels) and part of the shortest channel (16 channels; Fig. 1(c)). The sampling frequency was 5.3 Hz. For the co-registration of the NIRS data to the T1-MRI, the surface of the subject's face, three fiducial markers (nasion, left, and right preauricular points), and the positions of the probes, were all acquired using a hand-held laser scanner and a stylus marker (FastSCAN Cobra; Polhemus, USA).

2.4. MRI and fMRI data acquisition

Anatomical MR images were acquired for construction of individual head models, and functional images were acquired for evaluation of the reconstructed DOT images. All MRI images were acquired on a 3T Magnetom Trio Tim scanner (Siemens Medical Systems, Erlangen, Germany). T1-weighted anatomical images were acquired with an MPRAGE sequence (TR = 2250 ms, TE = 3.06 ms, flip angle = 9° , inversion time = 900 ms, FOV = 256 mm, matrix = 256×256 , voxel size = $1 \times 1 \times 1$ mm) and functional images were acquired using an echo planar imaging sequence (TR = 3 s, TE = 30 ms, flip angle = 80° , FOV = 192 mm, matrix = 64×64 , voxel size = $3 \times 3 \times 3$ mm).

2.5. fMRI data processing

Activation maps from the three task conditions were derived using the general linear model implemented in SPM8 (<http://www.fil.ion.ucl.ac.uk/spm/software/spm8/>). The image processing routine consisted of head motion correction, followed by mass-univariate linear regression, with the task–rest contrast for each task and the head motion parameters, entered as independent variables. The resulting T-value maps were thresholded ($p < 0.05$, FWE corrected) and percent signal maps for the three task conditions were also derived. The T-value maps and percent signal maps were then co-registered to each subject's T1 anatomical images and down-sampled to $4 \times 4 \times 4$ mm voxels for comparisons with the reconstructed DOT images. As the analysis was based on individuals' brains, we did not apply normalization to a standard brain.

2.6. NIRS data processing

The trial-averaged time series of the light intensity changes of the three wavelengths (780, 805, and 830 nm) were obtained from the raw continuous light measurement data using the following procedures:

1. Channels with a low voltage range were rejected (threshold: 5; number of rejected channels: 2.8 ± 1.6 channels).
2. Voltage data were converted to log-ratios using a base-10 logarithm.
3. A digital filter was applied to each run data (low-pass: Butterworth filter of order 7, cutoff 0.3 Hz; high-pass: Butterworth filter of order 3, cutoff 0.01 Hz).
4. ICA-wavelet motion artifact removal was performed on the filtered data. We first employed the logistic infomax ICA algorithm (binica.m in the EEGLab toolbox, <http://scn.ucsd.edu/eeglab/>, Delorme and Makeig, 2004) to the data, which consisted of all the measurement positions and wavelengths ($64 \text{ channels} \times 3$

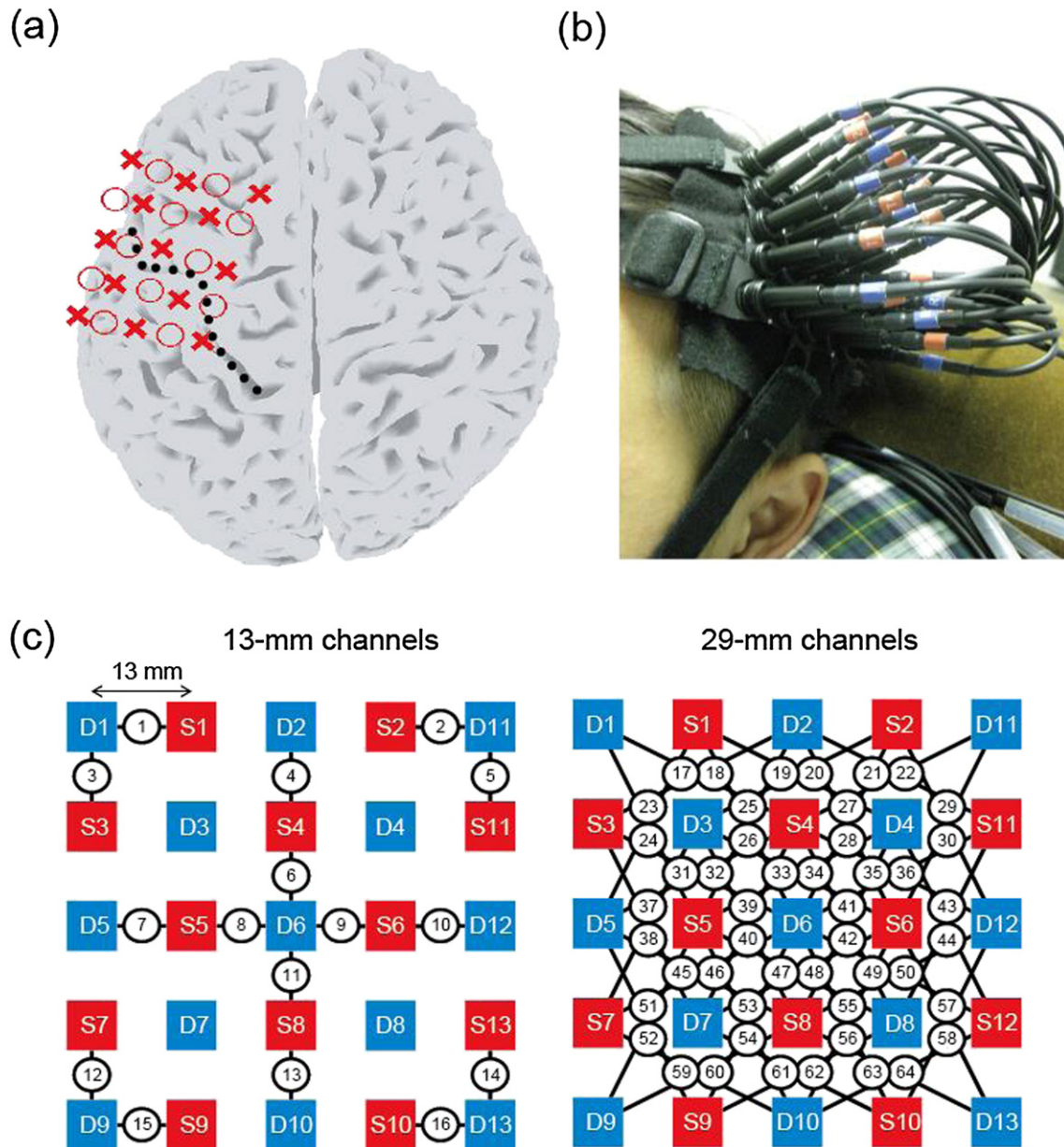


Fig. 1. High-density NIRS measurements. (a) Source and detector probes projected on a subject's cortical model. Circle and cross marks represent source and detector probes, respectively. Dotted line is the central sulcus along which the primary motor cortex is located. (b) Photograph of high-density NIRS measurement. (c) Channel configuration. Measurement channels consisting of source-detector pairs are represented by circles in the middle of the pairs (red: source, blue: detector).

wavelengths). This resulted in an un-mixing matrix and independent component time series. The modified version of the wavelet motion artifact removal algorithm (Molavi, 2012; `hmrMotionCorrectWavelet.m`; with a parameter $\text{iqr} = 3$ in the HOMER2 toolbox, <http://homer-fnirs.org/>) was then applied to the independent component time series. Finally, the light intensity data were reconstructed by applying the mixing matrix (inverse of the un-mixing matrix) to the processed independent time series. We applied the wavelet corrections to the independent time series, rather than the channel time series, to avoid correcting the time series of the three wavelengths independently.

5. Each run was segmented into trial data starting 8 s before the task onset and ending 35 s after the task onset.
6. The baseline of the data for each trial was adjusted to set the average amplitude during the pre-task period to 0.

7. For each of the three task conditions, outlier trials with a substantial deviation from the trial-median template were rejected (threshold: more than $2.5 \times$ the variance in the whole time series, number of rejected trials: 0.5 ± 1.5 trials).
8. The trial data from each task condition were averaged.

The resulting trial-averaged light intensity data were then used as input to the DOT image reconstruction algorithms.

2.7. DOT forward model construction

The forward modeling consisted of head model construction, NIRS probe co-registration, photon migration simulation, and sensitivity computation. An individual's head model was constructed by segmenting their T1 anatomical image into five tissue layers (scalp, skull, CSF, gray matter, and white matter) using FreeSurfer (<http://>

freesurfer.net/). The NIRS probe positions were then co-registered to the head model using an affine transformation. The rotation and translation parameters of the affine transformation were optimized so that a subject's facial surface, as measured by the laser scanner, matched that extracted from the T1 anatomical image. The photon migration process inside the head was simulated using Monte Carlo simulation software MCX (<http://mcx.sourceforge.net/cgi-bin/index.cgi>) with 10^9 photons. We used tissue optical parameters common to all three wavelengths (Table 1), as presented in a previous study (Fang, 2010). Finally, the sensitivity matrix, which related the absorption changes in the head tissue voxels to the light intensity changes at the source-detector pairs, was computed using Rylov approximation to the MCX results (Shimokawa et al., 2012). For computation of the sensitivity matrix, the $1 \times 1 \times 1$ mm voxel space was down-sampled to a $4 \times 4 \times 4$ mm voxel space in the reconstructed images. The image reconstruction region included the scalp and cortical voxels inside a 28-mm-deep cuboid, whose surface was a square along the scalp surface. This was obtained by extending the diagonals of the 5×5 NIRS probe square by a factor of 1.5.

2.8. Image reconstruction algorithm

For the image reconstruction, we followed the hierarchical Bayesian algorithm presented in Shimokawa et al. (2013), with two important modifications that were necessary to make the algorithm work robustly on datasets with varying signal-to-noise ratios (see discussion for details). The first modification was the use of informative priors for the cortical activity instead of non-informative priors. The parameters of the hierarchical prior distribution were set so that the confidence parameter γ_0 was 5, and the mean parameters $\bar{\lambda}_{0i}$ were the mean square values of the solutions obtained from the modified version of the depth-compensation minimum norm image reconstruction algorithm (see Appendix A for details). The mean parameters were also used for the initial values in the algorithm. This setting allows for a slight biasing of the resulting sparse image towards a minimum-norm image that is robust to low signal-to-noise levels. We set the confidence parameter $\gamma_0 = 5$, on the basis of an empirical exploration of the values of $\gamma_0 = 0.01, 0.1, 1, 5, 10, 100$ and observations that the group-level quantitative evaluation was very similar for $\gamma_0 = 5, 10, 100$, slightly inferior for $\gamma_0 = 1$, and clearly inferior for $\gamma_0 = 0.01, 0.1$. The second modification was an application of the approximation errors theory (Arridge et al., 2006) to absorb errors in forward modeling, such as probe co-registration error, tissue segmentation error, and photon migration simulation error. An additional model error term was also introduced to Eq. (2), which followed the Gaussian distribution with a variance of 4×10^{-6} for all the measurement channels, and for all the subjects. The algorithm iterations were stopped when the relative change of the objective function (free energy) was lower than 10^{-6} .

The modified depth-compensation minimum-norm algorithm for computing the initial value and the prior information of the hierarchical Bayesian algorithm required adjustment of two algorithm parameters: regularization and spatially-variant regularization. The regularization parameter, which controlled the balance between the data fit and the depth-compensation minimum-norm constraint, was automatically adjusted by maximization of a statistical criterion called the marginal

likelihood (or type II likelihood). The spatially-variant regularization parameter, which controlled the minimum sensitivity for depth-compensation, was set to an average sensitivity of around 20-mm depth from the scalp.

2.9. Image reconstruction evaluation

The reconstructed images were evaluated by comparison with the fMRI activation maps, which were considered as ground truth data. For evaluation of the DOT, the sign-inverted deoxygenated hemoglobin (HbR) images were used, rather than the oxygenated hemoglobin (HbO) images. This was because, in principle, the fMRI-BOLD signal varies according to paramagnetic agents, such as HbR (Ogawa et al., 1990), although some fMRI-NIRS studies showed empirical evidence that HbO-BOLD correlation was higher than HbR-BOLD correlation (Cui et al., 2011; Strangman et al., 2002).

The image reconstruction performance was quantified with four measures: the localization error (LE), area under the receiver-operating curve (AUC; Fawcett, 2006), spatial-pattern similarity (SS), and false positive amount (FPA). The LE signifies how well the main activity cluster in the fMRI is localized by the DOT. LE was computed as the distance between the center of mass of the main HbR activity cluster and the main BOLD activity cluster. We used a center of mass coordinate rather than a peak coordinate, as the localization error between two fMRI runs was smaller for the former case (mean values over all the subjects of 2.3 mm for the center of mass and 3.3 mm for the peak). AUC and SS indicate how well a spatial fMRI pattern is reproduced in the DOT. We computed AUC by regarding the fMRI T-map, thresholded at a p-value of 0.05 (FWE corrected), as the true binary image. SS was computed as the Spearman's rank correlation between the HbR image and the fMRI percent signal image. As computing LE, AUC and SS requires fMRI activations, these were evaluated for the HAND and FINGER conditions only. In addition, FPA was proposed to quantify spurious activation in a DOT image. The FPA was defined as the mean amount of negative HbR in the fMRI-null region (on voxels below the T-threshold). As the fMRI null region was defined using a positive T-value threshold, only negative HbR on fMRI-null voxels was averaged. The FPA allowed for quantification of the performance of the NO condition, where no fMRI activation was observed. Note that FPA was computed using HbR images before sign-inversion so that increasing BOLD activations are compared with decreasing HbR responses.

2.10. Image reconstruction methods for comparison

For comparison purposes, three DOT images were computed for each dataset. The first method used our hierarchical Bayesian algorithm mentioned previously (denoted as HB, hereafter). The second method was the modified depth-compensation minimum-norm algorithm (denoted as MN), which was used as the initial value and prior information of the HB method.

The third reconstruction used the current standard method developed in Washington University (denoted here as MN-WU), which has been previously validated using a variety of experimental datasets (Eggebrecht et al., 2014; White et al., 2009; Zeff et al., 2007). The NIRS process pipeline and image reconstruction algorithm presented in the supplementary materials of Eggebrecht et al. (2014) were followed. In

Table 1
Optical parameters in head tissue types (common to 780, 805 and 830 nm).

Tissue types	Absorption coefficient μ_a (mm^{-1})	Scattering coefficient μ_s (mm^{-1})	Anisotropy (g)	Refraction index (n)
Scalp & skull	0.019	7.8	0.89	1.37
CSF	0.004	0.009	0.89	1.37
Gray matter	0.02	9.0	0.89	1.37
White matter	0.08	40.9	0.84	1.37

brief, the NIRS process pipeline involved channel rejection, conversion to log-ratio, 0.01 Hz high-pass filtering, scalp artifact removal using global average of the short separation channel signals and regression, 0.3 Hz low-pass filtering, ICA-wavelet motion artifact removal, trial segmentation, trial rejection and trial-averaging for each task condition. The image reconstruction algorithm applied was the original depth compensation minimum norm algorithm (Culver et al., 2003), with the spatially variant parameter $\beta = 0.1$ and the regularization parameter α determined by the marginal likelihood of each data set (see Appendix A). A data-dependent α was adopted, rather than a fixed value of $\alpha = 0.01$, as presented in Eggebrecht et al. (2014), as the dependent case was superior in the group-level performance evaluation. The reconstructions were constrained to all voxels in either the scalp or cortex (Eggebrecht et al., 2012).

3. Results

3.1. fMRI results

To determine the reliability of the activation maps used as ground truth data, we first evaluated the consistency of the activation maps between runs 1 and 2. For the HAND condition, the reproducibility of the left M1 activity, as measured by the Pearson correlation, was very high for all the subjects (0.88 ± 0.07). For the FINGER condition, the reproducibility was very high (0.78 ± 0.11), except for one subject who showed almost no activity in one run, resulting in a low correlation coefficient of 0.11. We therefore excluded this subject from the evaluation of the FINGER condition. For the NO condition, none of the subjects showed any significant activity ($p < 0.05$, FWE corrected) in either run. With consideration of these results, we combined the data of runs 1 and 2, to obtain one activation map for each task condition for the DOT image evaluation. The sizes of the above threshold clusters in the HAND and FINGER conditions were 3472 ± 1582 , and $1389 \pm 1288 \text{ mm}^3$, respectively, and the largest T-values of the M1 activities were 27.3 ± 5.1 and 17.4 ± 3.9 , respectively.

3.2. NIRS results

The trial-averaged HbO and HbR data, measured with 13- and 29-mm channels for the HAND condition of subject 12, are plotted in Fig. 2. With the 29-mm channels, sensitive to cortical activity, task-related waveforms typical of those observed in the fMRI block paradigm were localized to the middle to posterior channels. On all the 13-mm channels, in which the sensitivity was dominated by scalp activity, non block-like waveforms were observed. We found uniformity of waveforms on the 13-mm channels in most of the datasets, including the NO condition. The PCA analysis of the continuous light intensity data from the 13-mm channels revealed that in 69 out of 72 runs (12 subjects \times 6 runs), the first principal component explained more than 50% of the variance and more than one uniform index (Kohno et al., 2007), indicating that scalp activity was uniform rather than localized.

3.3. DOT results

We evaluated the reconstruction performance of the DOT algorithms by comparing the cortical HbR DOT images with the fMRI activation images. We first demonstrate the qualitative evaluations by plotting the DOT images and the DOT time series for one representative subject (subject 12) and then show a quantitative evaluation that summarizes the data from all the subjects. The cortical HbR-DOT images of the remaining 11 subjects and examples of HbO-DOT images are presented in the supplementary material.

The cortical HbR images reconstructed using the three DOT methods are plotted in Fig. 3, along with the fMRI T-value images. For visualization purposes, voxel based images were mapped onto the cortical surface using inverse distance weighting interpolation. All of the DOT

images were computed as average activities within a time window from 5 to 25 s after the task onset. The HbR images reconstructed using the HB method were consistent with the fMRI T-maps in all the conditions. The MN and MN-WU methods also succeeded in reconstructing the main cluster of activity along the central sulcus, with a similar accuracy to the HB method. However, spurious activities, which were not observed in the fMRI T-maps, were also reconstructed. Even in the NO condition, where no significant fMRI activity was observed, the MN and MN-WU methods reconstructed activity with an amplitude comparable to the HAND condition. This was because the depth-compensation property artificially enhanced the amplitude of deep activity, or activity on the edge of the reconstructed region. The LEs of the HB, MN, and MN-WU methods were 3.0, 5.4, and 6.2 mm for the HAND condition, and 8.0, 9.0, and 7.0 mm for the FINGER condition. The AUCs of the three methods were 0.92, 0.83, and 0.82 for the HAND and 0.82, 0.71, and 0.69 for the FINGER condition. The SSs of the three methods were 0.82, 0.70, and 0.72 for the HAND and 0.69, 0.47, and 0.44 for the FINGER condition. The FPAs of the three methods were -0.18 , -0.47 , and -0.45 for the HAND, -0.18 , -0.42 , and -0.40 for the FINGER and -0.007 , -0.12 , and -0.05 for the NO condition. The cortical HbO images resembled sign-inverted HbR images (see supplementary materials).

The time series of the cortical HbO and HbR concentration changes at the peak voxel are presented in Fig. 4. In the HAND and FINGER conditions, all three methods successfully reconstructed positive HbO and negative HbR changes, with durations of around 20 s, and onset delays of 5–7 s. This is indicative of the wash-out mechanism, which is considered to be the origin of task-related BOLD signal changes. In the NO condition, the HB method reconstructed images without activation, while the MN method resulted in activity patterns comparable to the HAND condition. The MN-WU method also resulted in some small false positive activity.

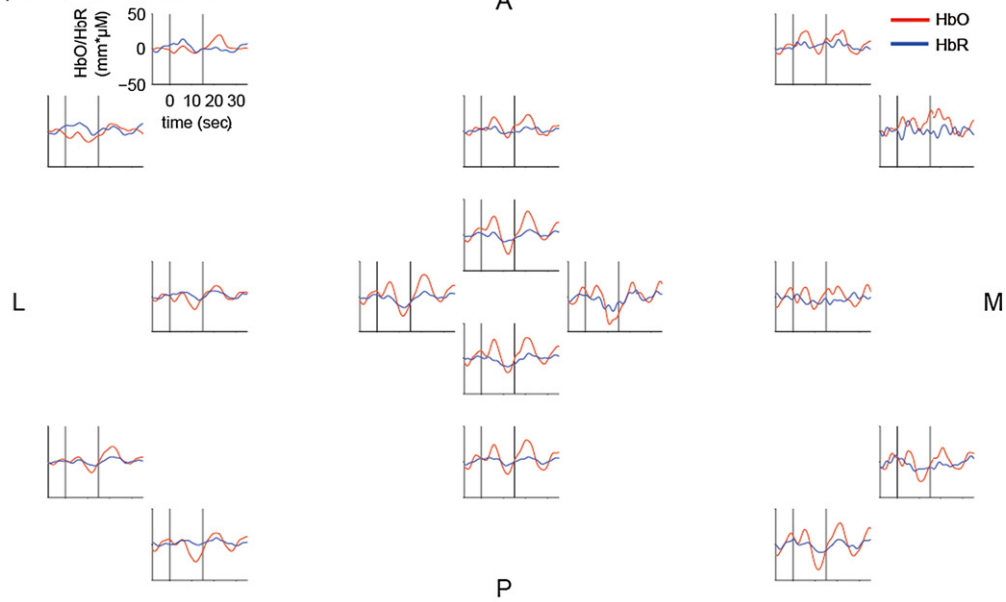
Scalp HbR images are plotted in Fig. 5. These images were computed by taking the root mean square values from the voxel-based images, within a time window from 5 to 25 s, and converting the values to the scalp surface images. The scalp image from the HB method is smooth; however, the MN image is less so and tends to have large values around the edge of the reconstructed region. The scalp HbO image showed the same tendency (see supplementary materials). The spatial smoothness of the HB reconstruction is not merely due to the prior information, as the parameter controlling smoothness was adjusted from the data.

In Fig. 6, the time series of the scalp HbO and HbR concentration changes for the four voxels just beneath probes D1, D9, D11, and D13 (Fig. 1) were plotted for the HB and MN methods. The scalp time series from one representative channel (channel 6), which was identified from the global average of the 13-mm channels, was plotted for the MN-WU method (all the 13-mm channels had identical scalp waveforms, but with different amplitudes). The temporal patterns resulting from the HB method showed little spatial variability, whereas those of the MN method were highly inhomogeneous. In particular, the waveforms of the D13 voxel (right-bottom panels), which were reconstructed using the MN method for the three task conditions, appeared random because of the influence of measurement noise from the nearby 30-mm channels. Conversely, the HB method was less influenced by measurement noise, and the reconstructed HbO waveform showed similarity with the scalp waveform identified from the global average of the 13-mm channels. However, we observed a discrepancy between the reconstructed HbR waveform and the scalp HbR waveform of the global average of the 13-mm channels. Two possible causes for this discrepancy are reduced accuracy of the scalp HbR reconstruction due to modeling error, and the influence of cortical contributions on the global average of the 13-mm channel.

We evaluated the reconstruction performance using four quantitative measures, LE, SS, AUC, and FPA (Fig. 7). We excluded any DOT

Subj.12 HAND

(a) 13-mm channels



(b) 29-mm channels

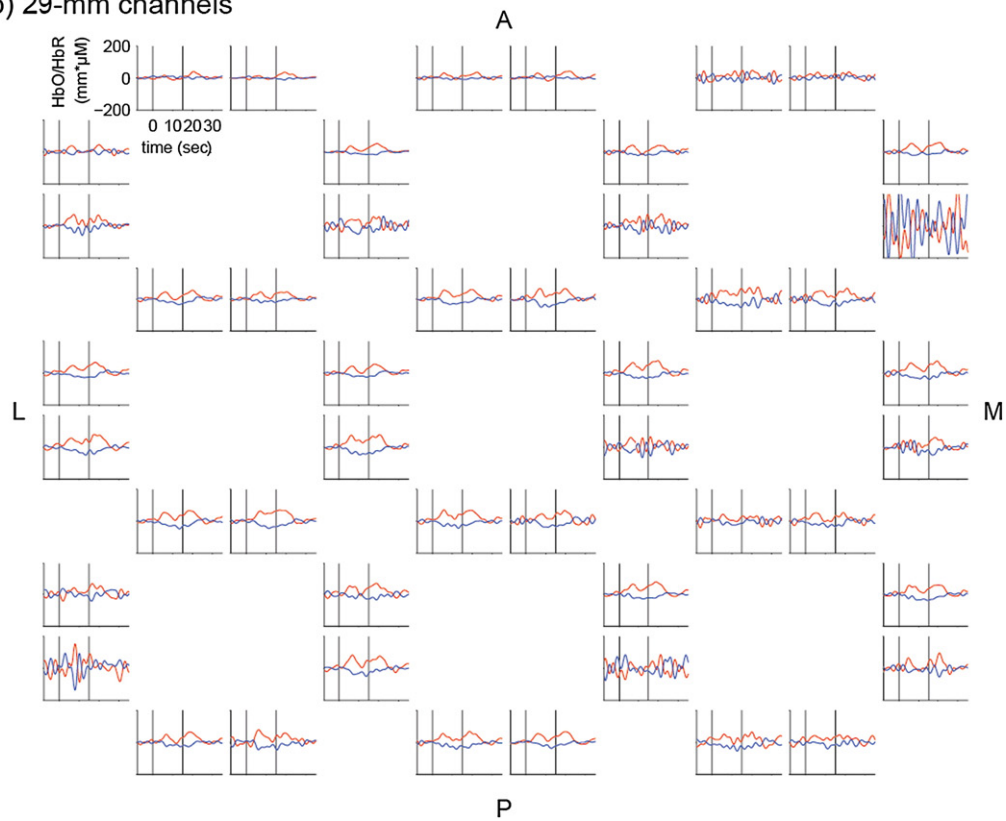


Fig. 2. Representative example of high-density NIRS data from subject 12 and the HAND condition. Trial-averaged HbO (red line) and HbR (blue line) waveforms of the 13-mm (a) and 29-mm channels (b) are plotted in each panel located on the center of corresponding source-detector pairs (see Fig. 1(c)). Two vertical lines inside each panel indicate task onset and offset. A = anterior, P = posterior, M = medial, L = lateral.

images that all three methods failed to reconstruct. We judged a method as a failure when one of the following three conditions was satisfied: an LE exceeding 15 mm, an AUC at chance level, or an SS at chance level. With these criteria, none of the 12 subject reconstructions failed in the HAND condition, but two of the 11 subject reconstructions failed in the FINGER condition. Compared with the MN and MN-WU

methods, the HB method achieved comparable LE scores, and significantly better SS and AUC scores in the HAND condition, while performance was better overall in the FINGER condition (Wilcoxon's sign rank test). The HB method achieved the best FPA scores for all the conditions. These results were consistent with the results of the qualitative evaluation of the cortical DOT images (Fig. 3 and

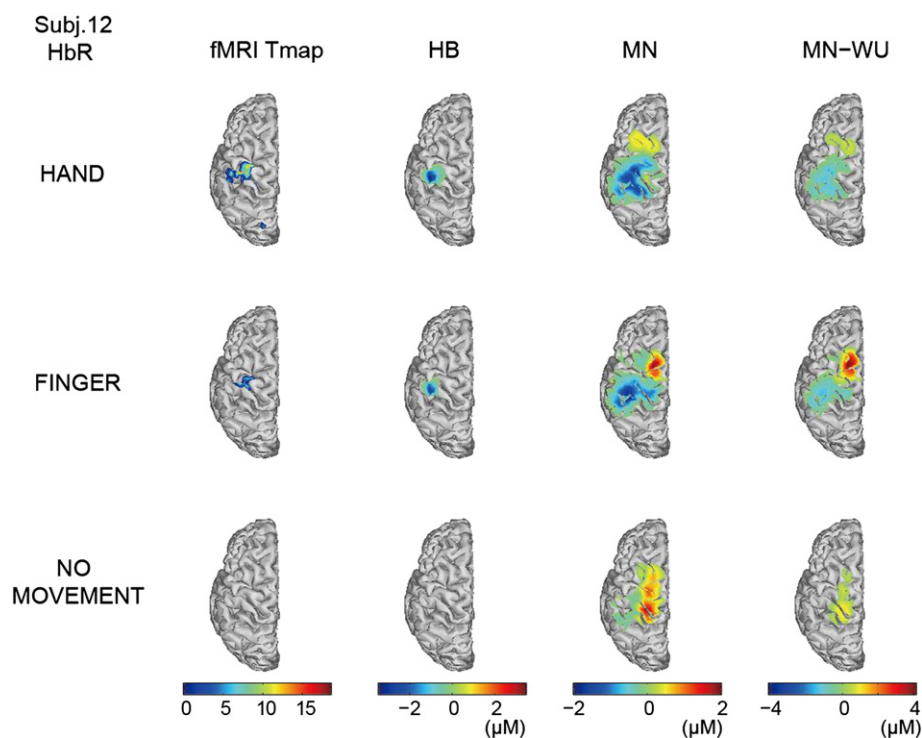


Fig. 3. Cortical activation maps of fMRI T-value and reconstructed HbR concentration changes from subject 12 in the three task conditions. In fMRI T-maps, activity over the threshold $T = 5.35$ ($p = 0.05$, FWE corrected) is shown. The three HbR images are averaged over a time window from 5 to 25 s after task onset. Only the left hemisphere is shown.

supplementary figures), where all three methods localized the main activity clusters, but the MN and MN-WU methods tended to also reconstruct false positives. The median scores of the four measures are summarized in Table 2.

Finally, we investigated the quantitative relationship between the reconstructed HbR and BOLD signal changes. We summated the (sign-inverted) HbR concentration changes and BOLD percent signal changes, of the main cluster of activity for each subject. The relationship was quantified by examining the Pearson correlation between the HbR and

BOLD across subjects. For the HAND and FINGER conditions, the HbR change reconstructed using the HB method showed the greatest proportionality to the BOLD signal changes, as shown in Fig. 8. The cross-subject correlation coefficients for this method were 0.82 and 0.69 for the HAND and FINGER tasks, while those of the MN and MN-WU methods were less than 0.5 in both tasks. No quantitative relationship for the NO condition was expected, as the main clusters of activity in the fMRI and DOT techniques were not located in corresponding regions.

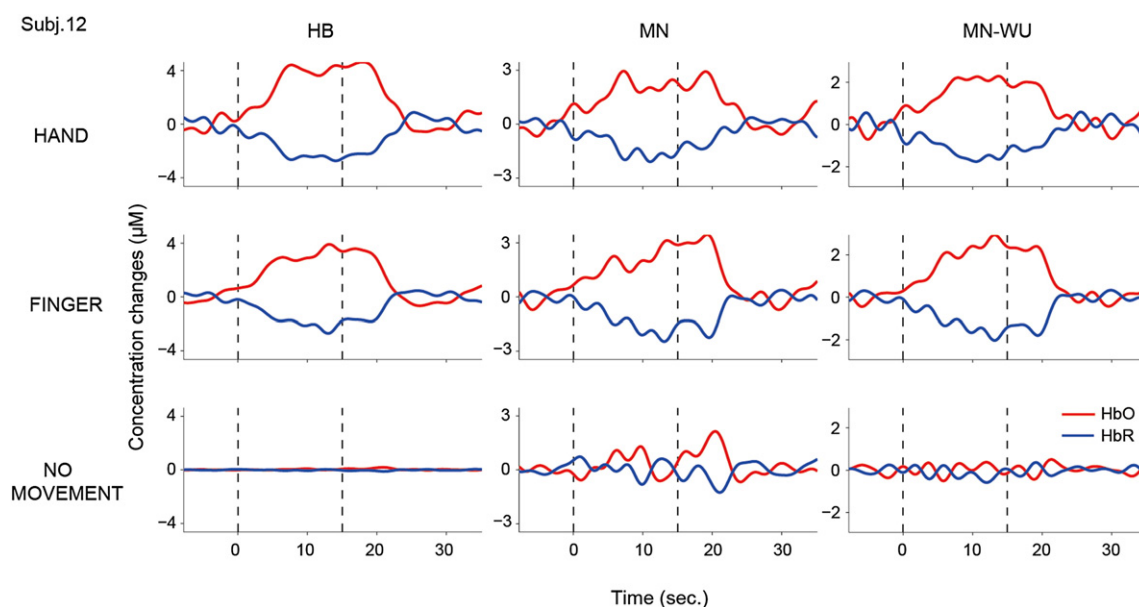


Fig. 4. Time series of reconstructed cortical HbO/HbR concentration changes at the peak voxel on left primary motor cortex in subject 12, for the three task conditions. In each panel, reconstructed HbO/HbR time series (red/blue lines) are plotted. Vertical dotted lines represent task onset and offset. The same y-range is used across task conditions.

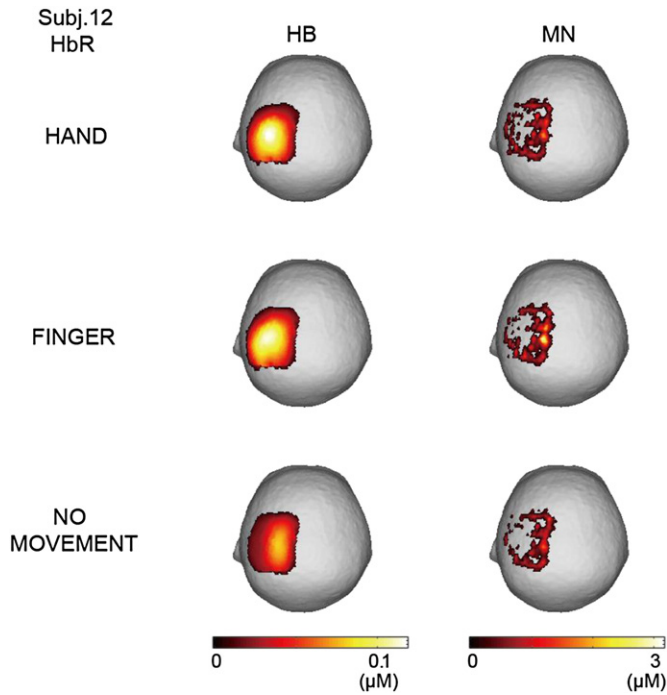


Fig. 5. Scalp activation maps of reconstructed HbR concentration changes from subject 12 in the three task conditions. Each HbR image is the root-mean-square image over a time window from 5 to 25 s after task onset.

4. Discussion

We report on the multi-subject and multi-task experimental validation of our HB DOT image reconstruction algorithm, using fMRI as a reference. We also compared the HB algorithm with the current standard MN-WU method for DOT image reconstruction (Eggebrecht et al., 2014). Compared with this current standard method, the HB showed

fewer false positives, which resulted in greater spatial-pattern similarities with the fMRI results, although differences in localization of the main peak activities between fMRI and DOT were comparable for both DOT reconstruction techniques. Additionally, the HB method achieved substantially greater cross-subject correlation between the total quantity of HbR change and the total BOLD signal percent change, indicating it was quantitatively more reliable. Compared with the BOLD signals, the HB achieved an LE of 6 mm and an SS of 0.6 for the HAND condition, and an LE of 8 mm and SS of 0.4 for the FINGER condition. The HB algorithm did not result in any significant activity in the NO condition, a condition that was expected to result in an absence of activity. We also confirmed the HB reconstruction performance did not degrade using only two wavelength data which most of the commercially available fNIRS/DOT systems employ (see supplementary).

A comparison with the current standard method of DOT reconstruction revealed performance improvements with the HB algorithm. The HB method is different from the standard method in two main respects. First, the HB method simultaneously reconstructs scalp and cortical activities within the DOT framework, whereas the standard method reconstructs cortical activity using a two-step method where the scalp contribution is removed by the short-channel linear regression, followed by image reconstruction of the cortical activity. This two-step method may cause problems when the distance of the short-channels is not sufficiently short. In this case, the shortest channels will be sensitive to part of the cortex, and the short-channel linear regression method will remove not only the scalp activity, but also part of the cortical activity. In our dataset, in four of the 12 subjects, the 13-mm channels had a not insignificant cortical sensitivity (more than 10%). Second, the HB method uses a sparse-promoting prior for prior information on cortical activity, whereas the standard method uses a depth-compensation L2-norm minimum norm prior. The sparse-promoting prior provided more focused cortical DOT images than the standard method; the standard method's depth-compensation is sometimes problematic as it artificially increases the amplitude of voxels with low sensitivity. With the MN-WU method, we frequently observed large activations in voxels near the boundary of the estimated region. These were not observed

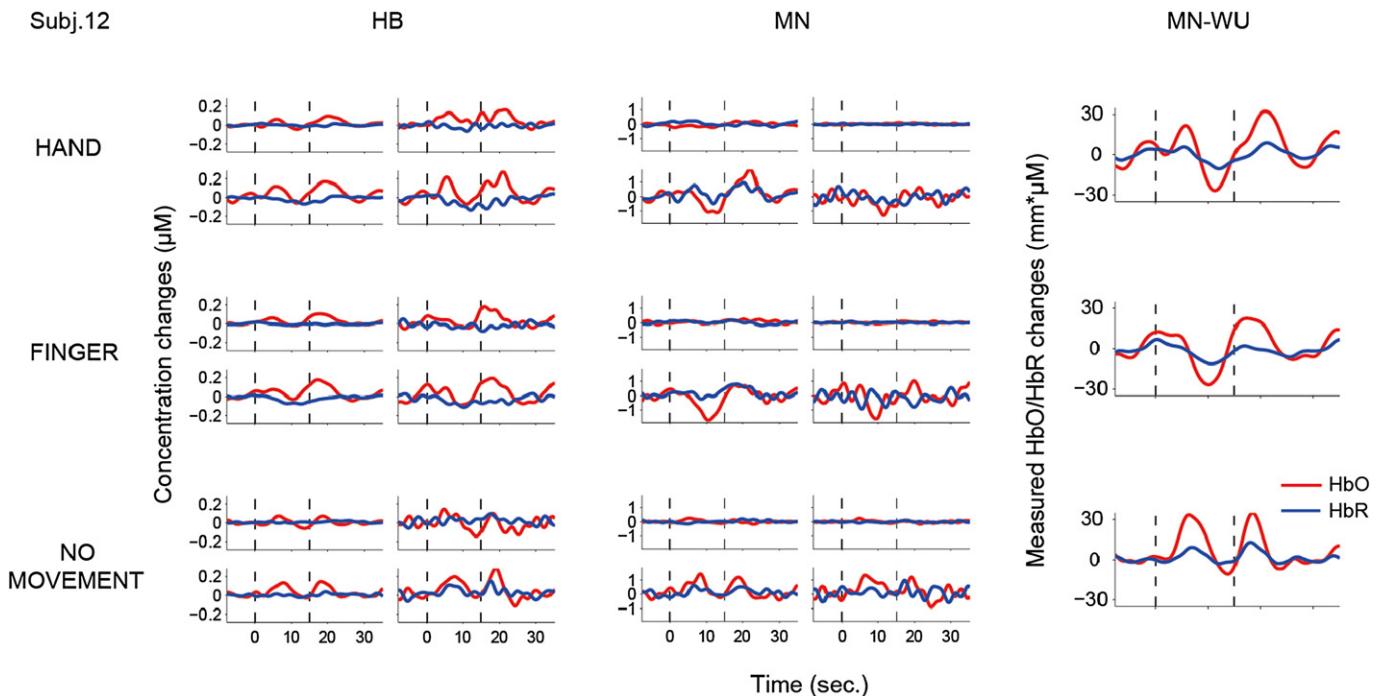


Fig. 6. Time series of reconstructed scalp HbO/HbR concentration changes from subject 12 in the three task conditions. First and second columns show scalp HbO/HbR waveforms (red/blue lines) from four scalp voxels just beneath the four probes D1, D11, D9, and D13, reconstructed by the HB and MN methods. The third column shows the scalp HbO/HbR waveforms from one representative channel (channel 6) removed by the short-channel regression in the MN-WU method. Vertical dotted lines represent task onset and offset. The same y-range is used across task conditions.

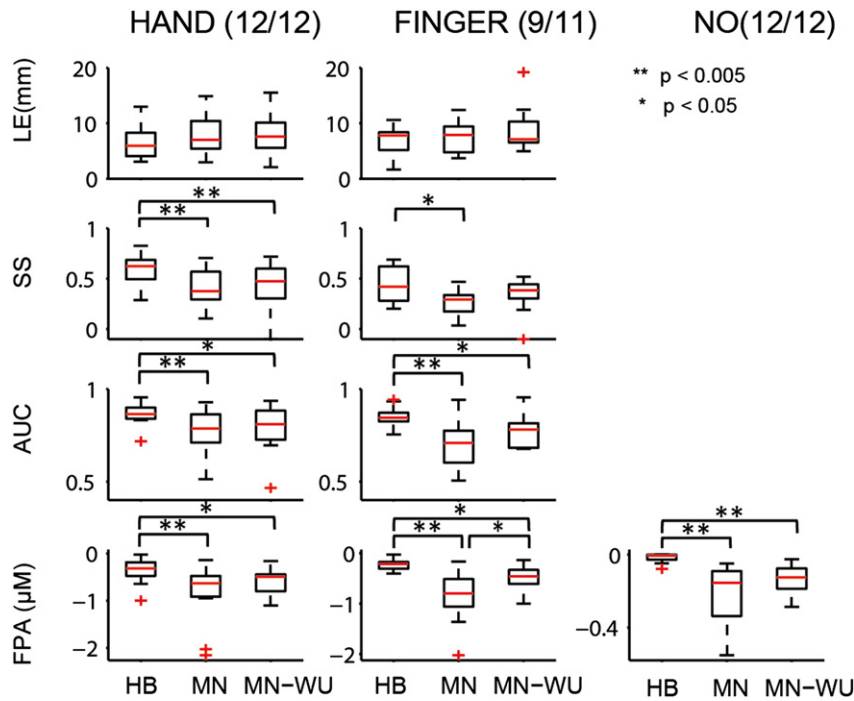


Fig. 7. Group-level reconstruction performance evaluated using four quantitative measures: LE, SS, AUC and FPA (from top to bottom rows). In the first and second columns, distributions of the four measures for HAND (all 12 subjects) and FINGER conditions (9 subjects) are shown using boxplots. In the third column, FPA for the NO condition (12 subjects) is shown.

in the fMRI images and less frequently in the HB-DOT images (see supplementary figures).

We added two important modifications to the HB algorithm that was described in our previous studies. These were to improve the robustness of the algorithm to datasets with different signal-to-noise ratios. The first modification was to use informative priors for the cortical activity, instead of (nearly) non-informative priors, which were used in the previous simulated data and single human case study. In the previous studies, we used a non-informative prior by setting the confidence parameter γ_0 to 0, or a very low value. This setting resulted in accurate sparse DOT images when the signal-to-noise ratio of the data was high. However, in this study we observed incorrectly localized sparse DOT images in some subjects when the data had a low signal-to-noise ratio. To resolve this issue, we adopted the informative prior, which slightly biases the resulting sparse image to a depth-compensation minimum-norm image that is more robust to low signal-to-noise ratios. The value of γ_0 determining the balance between the data and the prior information is an important parameter affecting the reconstructed images. Although we used a common parameter for all the subjects, it would be interesting to determine the optimal value for each subject and dataset, to facilitate optimal reconstruction of each individual DOT image. We did attempt to determine the optimal value using statistical criteria such as free energy, model evidence and

DIC (Gelman et al., 2014); however, we failed to find a technique for determination of the optimal parameter, even for the simulated data. Determination of the optimal γ_0 value is still a problem requiring further work.

The second modification was adoption of the approximation errors theory (Arridge et al., 2006) to absorb errors in forward modeling. In some subjects, we observed waveforms resembling sign-inverted cortical waveforms in the reconstructed scalp activity. This happened because the algorithm put too much emphasis on fitting to data from the 13-mm channels, as the noise variance of these channels, which was estimated from the fluctuations of the pre-task period, was too low. Such excessively low variance in the 13-mm channels is not problematic if there are no error factors in the forward modeling. However, in the real experimental data, several error factors were found, such as probe co-registration, tissue segmentation and photon migration simulation errors. If these error factors are not taken into consideration, the noise variance of the 13-mm channels may be underestimated, and cause overfitting of the 13-mm channel data by adjustment of scalp absorption change. To avoid this phenomenon, we introduced an additional model error term to Eq. (2), which follows the Gaussian distribution, based on the approximation error theory. In this study, we determined the variance from a single subject's data value as 4×10^{-6} , by observing the sign-inverted cortical waveforms in the scalp layers, while gradually increasing the value, and selecting a value when the sign-inverted cortical waveforms disappeared. Although the optimal model error variance may differ between subjects, we applied the same value to all subjects. Determination of the model error variance in an objective and systematic way is a practically important problem for future work.

Whether our spatial smoothness assumption for scalp activity is generalizable to other NIRS experiments requires further experimental evidence. Our short-channel PCA analysis revealed the homogeneity of scalp activity above the left primary motor cortex, regardless of the task conditions. Several previous studies have supported the finding of spatial smoothness in scalp activity in the motor and visual cortices (Gregg et al., 2010; Kohno et al., 2007; Zhang et al., 2005). However,

Table 2

Summary of the group-level quantitative evaluation (median and mean absolute deviation).

		HB	MN	MN-WU
HAND	LE	5.9 ± 2.4	7.0 ± 3.7	7.6 ± 3.1
	SS	0.62 ± 0.12	0.38 ± 0.15	0.47 ± 0.19
	AUC	0.86 ± 0.04	0.79 ± 0.09	0.81 ± 0.13
	FPA	−0.31 ± 0.13	−0.63 ± 0.19	−0.49 ± 0.10
FINGER	LE	7.8 ± 2.2	7.9 ± 2.4	7.1 ± 3.2
	SS	0.42 ± 0.16	0.29 ± 0.10	0.38 ± 0.13
	AUC	0.84 ± 0.04	0.71 ± 0.11	0.78 ± 0.13
	FPA	−0.21 ± 0.04	−0.80 ± 0.25	−0.46 ± 0.12
NO	FPA	−0.005 ± 0.005	−0.16 ± 0.09	−0.13 ± 0.05

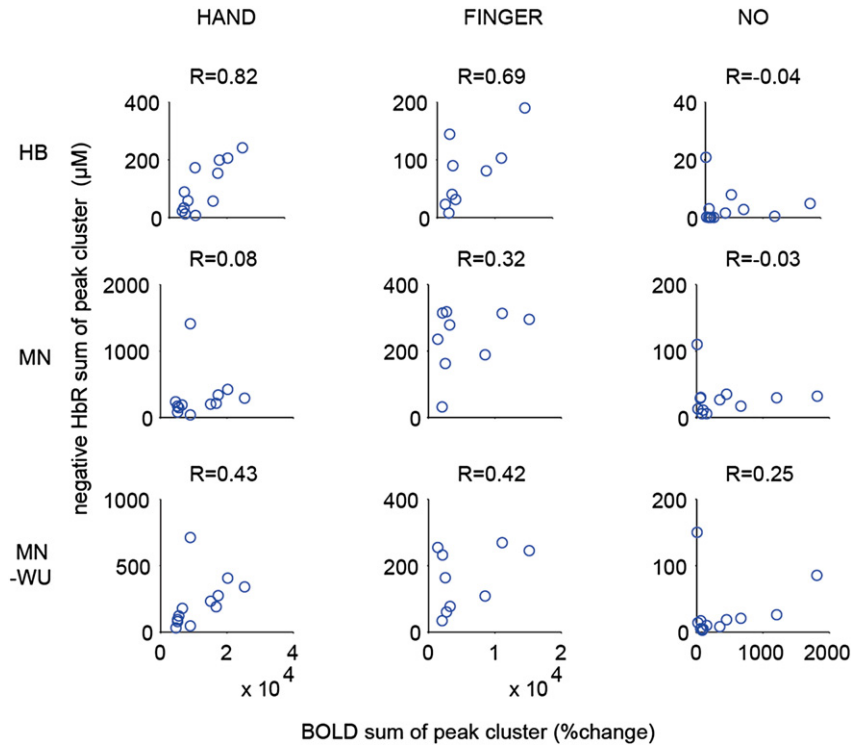


Fig. 8. Quantitative relationship between total HbR (sign-inverted) and BOLD signal changes in main activity clusters across subjects. Total HbR changes of main activity clusters reconstructed by the HB, MN and MN-WU methods are plotted against total signal percent changes of BOLD signals for the task conditions, HAND, FINGER, and NO. A point in each scatter plot corresponds to data from one subject. The R-value on the top of each panel is the Pearson correlation between the HbR and BOLD sum, to indicate the linear quantitative relationship between total HbR and BOLD changes.

in one paper the authors reported inhomogeneity of the scalp activity around the left motor cortex during a finger tapping task (Gagnon and Cooper, 2012). The prior information used for scalp activity should be revised with accumulated experimental evidence.

Evaluation of the whole procedure of image reconstruction, which consists of forward modeling and the image reconstruction algorithm, is a difficult problem. We focused on evaluating the latter reconstruction part in this study. How different parts of the forward modeling such as tissue segmentation methods, sensitivity computation methods and use of the standard brain (Custo, 2010; Ferradal et al., 2014) affect image reconstruction performance requires investigation. In particular, optimization of the whole procedure, taking both accuracy and time into account, is essential to make the DOT technology practically useful (Dehghani et al., 2008; Jermyn et al., 2013).

In summary, this study showed the feasibility of applying our HB algorithm to wider subject populations and wider task conditions. It also demonstrated its superiority over the standard DOT algorithm. We are now investigating applicability of our algorithm to brain network studies.

Acknowledgments

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Appendix A. Image reconstruction algorithm

This appendix describes the image reconstruction algorithm used in this study. Note that the algorithm below considers one wavelength for simplicity.

The following mathematical notations are used. The i -th element of a vector \mathbf{x} , i -th element and i -th row of a matrix X are denoted by $(\mathbf{x})_i$, $(X)_{ii}$ and $(X)_{i\cdot}$, respectively. The transpose of a vector \mathbf{x} is denoted by \mathbf{x}' . An operator $\text{diag}(\mathbf{x})$ denotes a diagonal matrix whose diagonal elements are given by $(\mathbf{x})_i$. An operator $\text{mean}_t \mathbf{x}_t$ denotes mean of \mathbf{x}_t with respect to t . A dot product $\mathbf{x} \cdot \mathbf{y}$ denotes an element-wise multiplication of two vectors \mathbf{x} and \mathbf{y} . The identity matrix is denoted by \mathbf{I} .

In the following we use the variables defined in the "Hierarchical Bayesian image reconstruction model" section. We further define the partition of image \mathbf{x} and sensitivity \mathbf{A} to scalp and cortical voxels $\mathbf{x} = [\mathbf{x}^s, \mathbf{x}^c]$, $\mathbf{A} = [\mathbf{A}^s, \mathbf{A}^c]$, and \mathbf{I}_{task} : an index set of time points during task, T : the number of time points during task, N_s, N_c : the number of scalp and cortical voxels, respectively.

A.1. Depth compensation minimum norm

The MN-WU image reconstruction algorithm is briefly described, and follows the supplementary materials of Eggebrecht et al. (2014).

An MN-WU DOT image is obtained by minimizing the following cost function with the depth-compensation regularization:

$$E(\mathbf{x}) = (\mathbf{y} - \mathbf{A}\mathbf{x})'(\mathbf{y} - \mathbf{A}\mathbf{x}) + \alpha \mathbf{x}' \mathbf{D}_1 \mathbf{x} \\ \mathbf{D}_1 = \text{diag}(\boldsymbol{\rho}_1 + \beta) \\ (\boldsymbol{\rho}_1)_i = (\mathbf{A}\mathbf{A}')_{ii}$$

To avoid overcompensation for near-zero-sensitivity voxels, the spatially-variant regularization β was set to 0.1. Minimization of the cost function leads to an MN-WU DOT image as

$$\mathbf{x}_{\text{MN-WU}} = (\mathbf{A}'\mathbf{A} + \alpha \mathbf{D}_1)^{-1} \mathbf{A}'\mathbf{y}.$$

For a measurement $\mathbf{y}(t)$ at time point t , we obtain a DOT image $\mathbf{x}_{\text{MN-WU}}(t)$. The regularization parameter α is automatically determined by maximizing the marginal likelihood using all the measurements

included in \mathbf{I}_{task} . The estimated median α over the subjects was 2.0, 2.1, and 7.2 for the HAND, FINGER and NO conditions, respectively.

A.2. Modified depth compensation minimum norm

An MN-DOT image is obtained by minimizing the following cost function with the modified depth-compensation regularization:

$$\begin{aligned} E(\mathbf{x}) &= (\mathbf{y} - \mathbf{A}\mathbf{x})' \Sigma^{-1} (\mathbf{y} - \mathbf{A}\mathbf{x}) + \alpha \mathbf{x}' \mathbf{D}_2 \mathbf{x} \\ \mathbf{D}_2 &= \text{diag}(\rho_2 + \beta) \\ (\rho_2)_i &= (\mathbf{A}' \Sigma^{-1} \mathbf{A})_{ii}. \end{aligned}$$

The value of β was set to $\text{mean}_{v \in \mathbf{I}_{20\text{mm}}}(\rho_2)_v$ where $\mathbf{I}_{20\text{mm}}$ is a voxel index set whose depth from the scalp is around 20 mm. Minimization of the cost function leads to an MN-DOT image as

$$\mathbf{x}_{\text{MN}} = (\mathbf{A}' \Sigma^{-1} \mathbf{A} + \alpha \mathbf{D}_2)^{-1} \mathbf{A}' \Sigma^{-1} \mathbf{y}.$$

The modified algorithm is identical to the original depth compensation minimum-norm algorithm when the measurement noise covariance matrix $\Sigma = \mathbf{I}$. For a measurement $\mathbf{y}(t)$ at time point t , a DOT image $\mathbf{x}_{\text{MN}}(t)$ is obtained. The regularization parameter α is automatically determined by maximizing the marginal likelihood using all the measurements included in the \mathbf{I}_{task} . The estimated median α over the subjects was 1.0, 0.8, and 3.5 for the HAND, FINGER and NO conditions, respectively. The spatially variant regularization parameter β was set to 2.3×10^4 , 2.3×10^4 , and 2.5×10^4 for the HAND, FINGER and NO conditions, respectively. When the modeling error was taken into account, the noise covariance Σ was replaced with $\tilde{\Sigma} = \sigma^{-1} \Sigma + m\mathbf{I}$ where $m\mathbf{I}$ is the modeling error term.

A.3. Hierarchical Bayesian image reconstruction algorithm

The HB algorithm sequentially updates a DOT image \mathbf{x} , the relevance parameter λ , and the scalp spatial smoothness parameter η , until the free energy converges. The HB image reconstruction algorithm when the measurement noise covariance is fixed to $\tilde{\Sigma} = \sigma^{-1} \Sigma + m\mathbf{I}$ where $m\mathbf{I}$ is the modeling error term (the scaling factor σ is not estimated) is described below.

The following notations are introduced for convenience; $\bar{\lambda}$, $\bar{\eta}$: the expectation of λ and η with respect to their variational posterior distributions, $\mathbf{z} = [\mathbf{z}^s, \mathbf{z}^c]$, $\tilde{\mathbf{A}} = [\mathbf{A}^s \mathbf{L}^{-1}, \mathbf{A}^c \mathbf{W}]$.

[Set Hyper parameters]

$$\begin{aligned} \gamma_0 &= 5 \\ \bar{\lambda}_{0i}^{-1} &= \text{mean}_{t \in \mathbf{I}_{task}} (\mathbf{x}_{\text{MN}}(t) * \mathbf{x}_{\text{MN}}(t))_i / \max(\mathbf{W}_{i \cdot} * \mathbf{W}_{i \cdot}) \end{aligned}$$

[Set initial values]

$$\begin{aligned} \bar{\lambda}_i^{-1} &= \bar{\lambda}_{0i}^{-1} \\ \bar{\eta} &= 10^{-7} \end{aligned}$$

Repeat [x step], [λ step], [η step] alternately until the relative free energy change becomes the pre-specified value (here 10^{-6}).

[x step]

$$\begin{aligned} \bar{\mathbf{z}} &= \mathbf{C}_z \tilde{\mathbf{A}} \tilde{\Sigma}^{-1} \mathbf{y} \\ \mathbf{C}_z &= (\tilde{\mathbf{A}}' \tilde{\Sigma}^{-1} \tilde{\mathbf{A}} + \mathbf{U})^{-1} \\ \bar{\mathbf{x}}^c &= \mathbf{W} \bar{\mathbf{z}}^c \\ \bar{\mathbf{x}}^s &= \mathbf{L}^{-1} \bar{\mathbf{z}}^s \end{aligned}$$

where $\mathbf{U} = \begin{bmatrix} \bar{\eta} \mathbf{L}' \mathbf{L} & \mathbf{0} \\ \mathbf{0} & \bar{\Lambda} \end{bmatrix}$, $\bar{\Lambda} = \text{diag}(\bar{\lambda}_1, \dots, \bar{\lambda}_{N_c})$ and $\bar{\mathbf{z}} = [\bar{\mathbf{z}}^s, \bar{\mathbf{z}}^c]$.

For a measurement $\mathbf{y}(t)$ at time point t , we obtain a DOT image $\bar{\mathbf{x}}(t)$ and $\bar{\mathbf{z}}(t)$. In [λ step], [η step] below, all images included in \mathbf{I}_{task} were

used to estimate $\bar{\lambda}_i$ and $\bar{\eta}$. The posterior covariance matrix of the scalp and cortical activities are, respectively, defined by partitioning the posterior covariance matrix \mathbf{C}_z :

$$\mathbf{C}_z = \begin{bmatrix} \mathbf{C}^s & \mathbf{C}^{s,c} \\ \mathbf{C}^{c,s} & \mathbf{C}^c \end{bmatrix}.$$

[λ step]

$$\bar{\lambda}_i^{-1} = w \left(\text{mean}_{t \in \mathbf{I}_{task}} (\bar{\mathbf{z}}^c(t))_i^2 + (\mathbf{C}^c)_{ii} \right) + (1-w) \bar{\lambda}_{0i}^{-1}$$

where $w = T/(T + 2\gamma_0)$. $T = 105$ in this study.

[η step]

$$\bar{\eta}^{-1} = \frac{1}{N_s} [\text{mean}_{t \in \mathbf{I}_{task}} \bar{\mathbf{z}}^s(t)' \bar{\mathbf{z}}^s(t) + \text{Trace}\{\mathbf{C}^s\}]$$

Appendix B. Supplementary data

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.neuroimage.2016.04.068>.

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